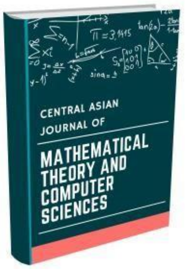

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Article

Walrus Optimizer Based Novel Energy-Efficient Clustering for Wireless Sensor Network

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Abstract: Wireless sensor networks (WSNs) have important role in modern Internet of Things (IoT) systems also make effective set of data as well as transmitting able. Although, energy sources restrictions in sensor nodes refers to basic concern, particularly in big-scale networks. Techniques based on clustering were presented as efficient concern for raising effectiveness of energy, however optimum clusters' shape is yet the essential study concern. In this paper, the new mechanism of clustering given the Walrus Optimizer algorithm is defined. Such algorithm, inspired by group walruses manner, optimizes formation and head selection cluster with decreasing energy use and balanced load share objective between nodes. Outcomes of simulation illustrate that presented technique given the Walrus Optimizer performs better than traditional algorithms like Genetic Algorithms (GA) also Particle Swarm Optimization (PSO) in case of network life and energy effectiveness. Specifically, the technique develops network lifetime by 13.45% and decreases use of energy by 10-15% in comparison with base techniques. Present study results illustrate Walrus Optimizer algorithm ability to solve main WSNs issues and paves the way for later study in applying nature-inspired mechanisms' domain in WSNs.

Keywords: Walrus Optimizer, Wireless Sensor Networks, Energy Efficiency, Clustering, Optimization Algorithms

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1. Introduction

WSNs became an important technology nowadays because of broad apps in different domains, such as security systems IoT, smart agriculture, environmental controlling [1]. WSNs are networks that some alike nodes of sensor (S.N.s) were interrelated and joined for transmitting data. That uses wireless connection for the aimed controlling and spreading data in space. WSN is usually used in aviation, environmental, industrial, medical as well as other environments because of its advantages including simple use, flexibility, low cost. Smart cities, homes, transport obtained broader-scale usages [2]. Such networks include nodes of sensor which gather environmental data then transfer them to basic station. Although, energy sources' restrictions in nodes of sensor refer to this technology's basic concern. As many nodes of sensor are empowered by non-rechargeable batteries and in a lot of terms replacing/recharging them is impossible, optimum use of energy is necessary for developing network lifetime [3].

An efficient energy management technique in WSNs refers clustering methods' usage. Clustering is the natural relations' identification process between objects and clustering them. Here, whole nodes' group is classified in sets/clusters on feature of node base'/desired parameters of network such as mutual distance of nodes, distance between nodes and base station (equal to sink), energy level as well as practicality of nodes. In its taxonomy, sensors could be grouped as CHs/member nodes. In a cluster, members are needed to generate packs of data then just link to the cluster head (CH) to transmit data. CH runs functions such as gathering data, aggregation app-driven processing. That transfers data of cluster to BS applying straight/ multi-hop strategy. So, clustering guarantees that just some nodes (CHs) bother from long-distance transmission overhead. Therefore, clustering degrades use of energy also develops whole lifetime of network. Also, that makes data collection able, later storing energy of nodes [4].

In the last few years, a lot of investigations were performed for clustering process optimization. Traditional algorithms like hybrid energy-efficient distributed (HEED) [6], low-energy adaptive clustering hierarchy (LEACH) [5] were presented basic developments to decrease use of energy, have restricted performance in case of optimization and long-term stability. In addition, meta-heuristic algorithms like genetic algorithm (GA) [8], ant colony optimization (ACO) [9] particle swarm optimization (PSO) [7] were presented for soling the issue. Generally, they are concerned.

In spite of the process, some gaps exist in study here. For instance, a lot of current techniques are not effective in balanced load share between nodes that causes quick depletion of energy in several nodes. Also, low convergence pace and computational complexity in several mechanisms provided their broad usage. At last, novel and modern algorithms review and assessment inspired by natural manners is yet not completely performed. Here, novel technique of clustering given the Walrus Optimizer algorithm [10] is presented that is inspired by social walruses manner. Such algorithm was promoted with purpose of decreasing use of energy, developing lifetime of network also balanced load share between nodes. Present study outcomes illustrate that presented technique could not just solve present concerns, but also outperforms the conventional algorithms, presents efficient solutions as well for developing WSNs efficiency. Present study's basic cooperation is as following:

a. Present study proposes the first Walrus algorithm app in WSNs clustering domain. Walrus algorithm, inspired by social and interactive walruses' manner possess great capability for looking for local and global optimum and presents optimum clustering via algorithms of exploration and exploitation.
b. In presented technique, the appropriate model of use of energy is modelled which not only take energy utilized in transferring and obtaining data into consideration, but also takes computational load and energy associated with data processing in nodes into consideration. Such model lets more general optimization.
c. Applying the processes which are optimum with simple structure, Walrus algorithm decreases computational complexity also develops pace of convergence in comparison with other techniques.
d. Presented technique is able to confirm big and small networks of sensor also could be applied in different scenarios which contain big nodes number.
e. Present paper compares our presented mechanism outcomes with other famous evolutionary mechanisms given the different parameters that illustrates that presented study is better than other state-of-art.
f. Statistical and experimental graphs show proposed efficiency of method in network lifetime, cluster count consistency, transmitting packet, energy use.

The following of this study is listed as: Section 2 briefly discusses relevant study work. Section 3 provides presented scheme for CH selection, Section 4 shows simulation research and confirms presented scheme. At last, section 5 presents outcome and presents insights for later study.

Related works

In the last few years, optimizing clustering and managing energy in WSNs have attracted a lot of investigators' attention. Optimum use of energy refers to one of the most essential concerns in such networks, due to that nodes of sensor normally apply restricted and non-renewable sources of energy. To this, clustering algorithms improvement which could decrease use of energy also develop lifetime of network is taken as one of the main study regions here. Here, we would particularly concentrate on nature-inspired mechanisms and check the app to WSNs issues. Every paper advantages and disadvantages would be analyzed.

In paper [11], the multiple Sparrow Search Algorithm with Differential Evolution algorithm is targeted in solving efficiency of energy by CH selection in WSNs. presented mechanism applies high-level Sparrow Search Algorithm search efficiency and dynamically Differential Evolution ability which develops nodes' lifetime time. Presented Improved Sparrow search algorithm applying Differential evolution model to select the best feasible CH illustrates residual power and throughput improvement rather than other compared mechanisms.

In paper [12], sensor nodes (SNs) are grouped here applying mechanism of Adaptive Sailfish Optimization (ASFO) with K-medoids. This study basic aim is optimizing CH selection via latency and distance decrease, energy stabilization among nodes. The energy-efficient cross-layer-based expedient routing protocol (E-CERP) is applied for assigning the shortest way, actively reducing overhead of network.

In paper [13], writers presented the CH selection which is energy-efficient applying the developed GWO (EECHIGWO) algorithm version for alleviating imbalance among exploitation and exploration, basic GWO algorithm premature convergence, shortage of population variety. This study basic aim in developing network stability, network lifetime, energy efficiency, medium throughput in WSNs with optimum CHs selection applying mechanism of EECHIGWO. That takes medium intra-cluster and sink distance, residual energy, CH balancing agent into consideration as parameters to choose CH.

In paper [14], writers provide QPSOFL, the protocol of routing and clustering which combines quantum PSO and system of fuzzy logic for developing prolong network lifetime as well as energy efficiency. QPSOFL uses developed quantum PSO mechanism for choosing optimum CHs using Sobol orders for diversifying population in establishment. Also, that cooperates Lévy fight and Gaussian position updates given the perturbation for avoiding trapping in local optima.

In paper [15], the developed levy chaotic PSO-based cluster routing protocol (LCPSO-CRP) is presented dynamically for IWSNs that efficiently extends lifetime of system. After that, chaotic optimization approach is modelled that highly develops pace of convergence and develops LCPSO-CRP search domain. In comparative test order, LCPSO-CRP has benefits over present protocols because of the two levy flight strategy and chaotic optimization approach distinctive use. Also, present study presents novel effective model of clustering routing for IWSNs, taking CHs energy, intra-cluster and BS distance as well as cluster members energy into consideration.

In paper [16], writers present the clustering model which is energy-efficient combined with PSO technique known as PSOEECS for WSNs for increasing energy efficiency when at the same time developing sensor nodes lifetime. Predominant issue being mentioned here refers to CH selection that aids collecting, aggregating and forwarding data from CH routing paradigm. PSO-EECS mechanism applied for fitness parameters optimization for CH selection that contain rate of energy, load balancing, distance considerations, Network's average energy, node density among other things.

In paper [17], provides new technique for routing given the cluster which makes process of routing more efficient for decreasing lifetime of network. It was performed under 2 steps: choosing optimum CH through novel Moth Levy adopted Artificial Electric Field Algorithm (ML-AEFA), transmitting data is performed by novel mechanism of Customized Grey Wolf Optimization (CGWO). Now, optimum CH selection is performed through taking death node time, distance among the sensor nodes also CH and BS, energy, node degree.

In paper [18], multiple strategy integrating ACO and ABC was raised. Present strategy aids in choosing optimum CH from terminals set. Some agents are taken in CH choice such as distance to BS also neighbors, nodes residual energy, node centrality and degree. ACO assigns a way among CH and BS through choosing the most effective way in case of node degrees, distance, the left power.

In paper [19], concentrates on 2 strategies, viz. Hybrid Butterfly and Ant Colony optimization algorithm with Static sink node (HBACS) as well as HBAC with Mobile sink node (HBACM) that is Butterfly Optimization (BOA) and ACO hybridization. BOA assigns optimum CH, ACO carries out the energy-efficient routing, then decreasing use of energy also increasing lifetime of network. In addition, here, sink node mobility is applied for removing multi-hop connection among nodes of sink as well as CHs, therefore, mentioning hot-spot concern and developing lifetime of network.

In paper [20], present the novel algorithm of clustering known as Energy Efficient Hybrid Clustering and Hierarchical Routing (EEHCHR) in WSN. Now, the novel adaptive and hybrid clustering model was presented for min node's energy use applying method of Fuzzy C-Means (FCM), Euclidean distance parameter, nodes residual energy, BS situation. Whole CHs are chosen applying fitness task that is energy efficient that works in adaptive path with nodes' residual energy for CH selection process development. For effective network's energy use, they provided the routing approach of hierarchical packet through defining DCH (Direct Cluster Head) and CCH (Central Cluster Head) meaning that are chosen through various tasks of fitness also work as the relay for some other CHs.

In paper [21], algorithm of PSO combined with energy efficient clustering and sink mobility ((PSO-ECSM) is presented for coping with issues of sink mobility and CH selection. Broad simulations of computer are performed for assigning PSO-ECSM performance. 5 agents like node degree, residual energy, energy consumption rate (ECR), distance, medium energy are taken for selecting CH. Such agents' optimum value is assigned via algorithm of PSO-ECSM. Further, PSO-ECSM mentions the issue of relaying traffic of data in multi-hop network through presenting mobility of sink. General review of literature is introduced in Table 1.

Table 1. The general review of literature in methods which are energy-efficient.

Ref	Technique	Year	Advantages	Limitations	Software used	Metrics
[11]	Hybrid Sparrow Search Algorithm with Differential Evolution	2022	Enhanced lifetime of nodes, improved residual power, and throughput	Increased computation al complexity	MATLAB	Residual energy, throughput
[12]	Adaptive Sailfish Optimization (ASFO) with K-medoids	2023	Energy stabilization, reduced distance and latency, shortest route with minimal	Scalability challenges in larger networks	NS2	Energy consumption, End-to-End Delay, network overhead, Network Lifetime,

			network overhead			Throughput, Packet Delivery Ratio (PDR), Packet Loss Ratio (PLR), Jitter
[13]	EECHIGWO: Improved Grey Wolf Optimization	2023	Enhanced energy efficiency, throughput, network stability, and lifetime	Premature convergence in highly dynamic networks	MATLAB	Energy efficiency, average throughput, network lifetime, stability
[14]	QPSOFL: Quantum PSO with Fuzzy Logic	2024	Better energy efficiency, prolonged network lifespan, avoids local optima	Complexity in integrating fuzzy logic with QPSO	MATLAB	Network lifetime, Network throughput, Energy consumption, Network scalability
[15]	LCPSO-CRP: Levy Chaotic Particle Swarm Optimization	2023	Prolonged system lifetime, improved convergence speed, expanded search space	Overhead due to chaotic optimization strategies	MATLAB	Network lifetime, energy consumption, Node average energy
[16]	PSO-EECS: Particle Swarm Optimization	2023	Optimized CH selection, load balancing, increased lifetime	Limited performance in dynamic topologies	MATLAB	Network longevity, Dead node vs rounds, Network’s remaining energy, Throughput, Network stability period
[17]	ML-AEFA: Moth Levy with Artificial Electric Field Algorithm	2022	Effective CH selection, improved data routing, maximized network lifetime	Complexity in integrating multi-phase optimization	MATLAB	alive nodes, residual energy, network lifetime, total packet transmitted to BS, throughput, packet drop ratio, Convergence, Error analysis, Computational time analysis

[18]	Hybrid Artificial Bee Colony (ABC) and Ant Colony Optimization (ACO)	2024	Ideal CH selection, efficient routing, minimized energy consumption	Higher computation al cost	MATLAB	FND, HND, LND, Live nodes, Average energy consumption, Total packets transmitted to the BS, Packet drops ratio
[19]	Hybrid Butterfly Optimization and Ant Colony Optimization (HBACS & HBACM)	2022	Optimal CH selection, resolves hot-spot issue, extended network lifetime	Increased complexity in sink mobility handling	NS2	Residual energy, Throughput, Number of alive nodes, Convergence rate, Load balancing analysis
[20]	EEHCHR: Energy Efficient Hybrid Clustering and Hierarchical Routing	2021	Adaptive clustering, efficient CH selection, hierarchical packet routing	Limited scalability in dense networks	MATLAB	Lifetime, Energy consumption of the network, Coverage
[21]	PSO-ECSM: Particle Swarm Optimization with Energy Efficient Clustering	2020	Efficient CH selection, optimized sink mobility, reduced data traffic overhead	Challenges in maintaining consistency in multi-hop networks	MATLAB	Stability period, network life time, number of dead nodes against rounds, network's remaining energy, and throughput/Number of data packets sent to sink)

From the previous table analysis, this could be observed that different techniques were presented for clustering and routing in WSNs, each of them has some benefits and restrictions. Multiple mechanisms like Sparrow Search Algorithm with Differential Evolution and Adaptive Sailfish Optimization (ASFO) concentrated on developing stabilization of energy, decreasing latency, and raising life of network, however simultaneously, they made high computational complexity. Mechanisms given the collective smartness PSO, ACO, GWO were efficient for balancing exploitation and exploration, however concerns like high computational costs as well as premature convergence are yet stable.

In general, present review illustrates that however essential process was made to develop WSNs energy and effectiveness, yet some chances exist for later development, particularly in case of decreasing computational complexity as well as raising flexibility in different scenarios of network. Such restrictions bold requirement for more novel mechanisms like Walrus Optimizer that could present better performance than present techniques through unique features exploitation.

2. Materials and Methods

Our presented technique is improved given the mechanism of WO that is modelled for developing effectiveness of energy, extending life of network, optimizing CH selection in WSNs (Fig 1). such technique is inspired by social walruses manner for efficiently searching for an issue region by integrating approaches of exploration and exploitation, that presents general response for clustering an managing energy.

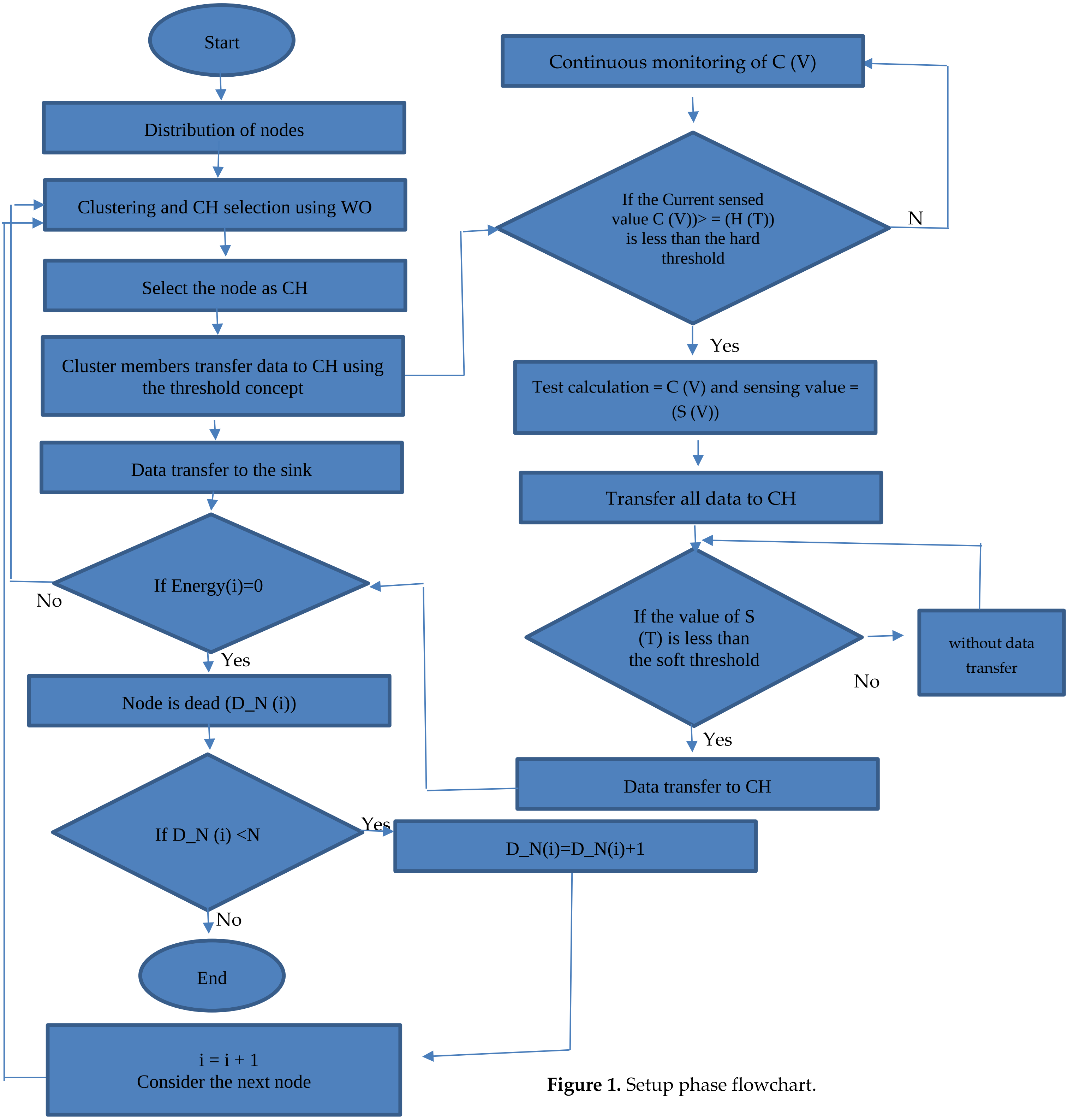


Figure 1. Setup phase flowchart.

Firstly, WSN is virtually simulated. Variables of clustering contain left nodes' energy, nodes density, cluster center and BS distance. WO mechanism simulates exploration (looking for basic cluster vertices), exploitation (optimizing cluster vertices selection) manners. Walruses go issue region and develop optimum responses applying approaches like collaboration and migration. By applying variables of clustering, the highest efficiency nodes in case of location and energy are chosen as CHs. The optimum selection decreases use of energy in clusters and balances load among nodes. After choosing CHs, transmitting ways of data to BS are optimized for obtaining the lowest energy use and feasible delay. Such optimization is performed through taking some agents into consideration like cluster member nodes' number, CHs energy, distance.

This path carries out in a way that WSNs contain nodes' number which are extended in region and nodes transfer info to center. Comprehensive aim is assigning CHs series which aim is being intermediary among nodes and BS, firstly, every node transfers info to CH after that to station. The aim is the way for assigning CHs at every stage due to that the selection leads them to firstly transfer observing message to others who are modelled as CHs. Second, gather whole messages and transfer them to BS with each other, it needs much energy, you have to consider how much energy is remained and distance of neighbors and clusters. Presented function is the same for every stage, CH is assigned is that leads to use of energy due to that should let others know of the situation and transfer them a control message which leads use of energy.

Presented protocol is a centralized protocol where BS monitors cluster shaping and CH selection process. The protocol is run in rounds number with two steps in every round that is the startup step and the steady condition step. In step of setup, cluster form station, the plan of CH selection and TDMA are decided. Step of steady condition is step of data transmission.

Here, whole nodes are estimated to be stabled. For instance, whole nodes are not mobile as they are located. In addition, this is estimated that every node of sensor creates a data packet in every circle to be transferred to BS for simplicity.

Startup step

Clusters' shaping as well as CHs selection refer to basic setup step aim.

(a) Initialization:

Entire network is organized here, for instance, the random heterogeneous node expansion that shapes heterogeneity of energy 3 classes is aimed in aimed region. Sink is located out of network for gathering data from network and transferring to customer through Internet. After that the expansion of node is done, nodes clustering is performed and CH selection for every cluster is carried out applying WO.

This must be considered that although function of clustering is usual, CH selection is performed applying 5 parameters that causes it to be satisfactory for obtaining life of network and long time of stability.

(b) Step of steady condition:

After that the step of setup is done, WO enters fixed step that happens among "inter-cluster and intra-cluster" and "CH and sink" connections.

This must be considered noted that task of WO contains different essential agents which take residual energy and basic energy into consideration that selects CH for nodes which are embedded with more energy in basic step and accessible energy for the function. Also, for energy use decrease by nodes because of agent of distance, nodes and sinks distance is taken as well.

Applying WO algorithm for optimum choice of CH

In this section, we apply WO for optimum choice of CH.

Presented technique mechanism with progress of confirmation that nodes are provided as group of walruses that are assessed later as bitstreams. Node condition is shown as CH while bit is "1", on the other hand, node is declared as node of member while bit value is "0". The process of validation aids progress of initialization therefore eligible nodes is taken for the next optimization stages.

Initialization

Progress of initialization obtains exploitation step after confirmation. Particular deer are initialized given the wanted features. Such parameters of network contain region of network, nodes' number, sink state in network, transmission and energy value obtained in transmitting data. After carrying out the basic stages, task of fitness is computed.

Fitness function

Function of fitness refers to different functional parameters aggregation which are integrated with formulating states which should be increased/decreased. Function of fitness copes with the different parameters of fitness which decide present unique fitness. Parameters of fitness applied in function of fitness function are as:

Fitness parameters (FP)

FP is computed based on present amount given the different agents. That must be considered that the more significant the parameter, the more optimized amount is achieved. Now, parameters of fitness are applied for decreasing use of energy also present network-to-network life. The parameters below are taken while improving function of fitness. Such parameters are taken for selecting CH in network and are mentioned below.

a. Node residual energy

One of the most prominent agents for considering in CH selection refers to node residual energy after every cycle. CH rotation agent reason is given the node residual energy. Rotating CH is needed for balancing energy in lattice. As taken network is naturally heterogeneous, node with max energy is considered to be chosen as CH. Here, residual energy rate to sum energy is taken. FP1st (first fitness parameter) that describes energy contract applying Eq. (1).

$$FP_{ist} = 1/\sum_{i=1}^{N}\left(\frac{E_{R(i)}}{E_T}\right) \tag{1}$$

In Eq. (1), total node i residual energy rate is shown by ER(i) and sum energy shown by ET is taken for FP1st assessment. Sum nodes' number with N. that is illustrated, the lower the FP1st amount for node, the less probably this is to be chosen as CH.

b. Medium node energy.

The other agent of energy is taken for choosing CH is medium node energy. Medium node energy is taken due to that network is developed with heterogeneous nodes of energy. So, high basic nodes of energy are considered for choosing CH. It is due to that super nodes last longer in comparison with developed nodes and likely developed nodes are considered over usual nodes. The second parameter of fitness shown by FP2nd is medium node energy as well as the amount is normalized among 0 and 1. In Eq. (2), E(i) is node i energy and N shows sum network nodes number.

$$FP_{2nd} = \frac{1}{N}/\sum_{i=1}^{N} E_{(i)} \tag{2}$$

c. Sink and node distance.

When nodes connect with every another/ sink, this is agent of distance which assigns communication node energy use. The smaller the distance among sink and node, the less energy is used by node. So, approaches of routing/CH selection take care of such parameter for reducing medium distance among nodes of sink and sensor. The third fitness parameter (FP3rd) is provided by Eq. (3) to model function of fitness for selecting CH contracts with agent of distance.

$$FP_{3rd} = \sum_{i=1}^{N} \left(\frac{D_{N(i)-S}}{D_{AVGN(i)-S}} \right) \tag{3}$$

FP_{3rd} computes total distance cost incurred for every first node that i ranges from 1 to N (sum nodes' number in network). In Eq. (3), D(N (i) – S) shows ith node Euclidean distance from sink, when DAVG(N (i) – S) shows medium distance among node and sink. This could be observed that the lower FP3rd amount decreases node selection as CH.

d. Neighbors number around node.

While region of network is big, intra-cluster communication is becoming the dominant entity. Node selection as CH when this does not depend in neighboring nodes number to the same node, that causes node selection as CH which is far from other nodes. So, node of CH would use more energy in data collection from other nodes in a cluster. Thus, for preventing this selection, neighboring nodes number is taken. So, fourth fitness parameter (FP4th) copes with neighboring nodes number and is described by Eq. (4) as the following.

$$FP_{4th} = \left(\frac{\sum_{i=1.j=1}^{N_{CL}} D_{(N(i)-N(j))}}{N_{CL}}\right) \tag{4}$$

That, D (N (i) - N (j)) shows distance among node i and the cluster jth node. NCL shows cluster nodes number. So, FP4th must be decreased for making that the energy-efficient CH selection.

e. Energy consumption rate (ECR)

It is the important agent which assigns node energy use also gets prominent issue for selecting CH. This is the difference among basic node energy as well as left node energy after the first cycle. Accordingly, since cycles' number goes on, node energy in the last cycle is changed to the basic energy. So, ECR is computed and compared with medium ECR threshold amount. When computed amount is less than medium amount of threshold, the node is eligible to become a CH, on the other hand, this is not eligible to become a CH for the same cycle. The fifth parameter of ECR fitness is provided by Eq. (5).

$$FP_{5th}(ECR) = \sum_{i=1}^{N} \left(\frac{E_{p(i)} - E_{RC(i)}}{E_{p(i)}} \right) / (E_{p(i)})) \tag{5}$$

That ERC (i) amount shows energy used in present cycle by node i and Ep(i) shows node i energy amount in the last cycle. For computing medium threshold of ECR for a node, node with the lowest cluster energy is taken. When each node uses huge energy amount and becomes less in amount in comparison with the lowest node of energy, this is not taken for choosing CH.

f. Network Fitness function

Network fitness function is different fitness parameters combination that are comprehensively combined in unique state as below in Eq. (6).

$$F = \frac{1}{\varphi \times FP_{ist} + \delta \times FP_{2nd} + \gamma \times FP_{3rd} + \alpha \times FP_{4th} + \sigma \times FP_{5th}} \tag{6}$$

Function of fitness shown by F in Eq. (6) must be decreased therefore performance of network obtains the desired amount. In Eq. (7), φ, δ, γ, α, σ weight coefficients are multiplied by related parameters of fitness. Such agents are equally weighted as Eq. (7).

$$\varphi + \delta + \gamma + \alpha + \sigma = 1 \tag{7}$$

So, basic aim task explained for WO is provided by Eq. (7). Functions based on WO are used for decreasing network life performance and raise time stability. This is essential for considering that however we presented WO algorithm. Although, when taking formulation of fitness function which takes different parameters of fitness, aim performance is taken for optimizing that is explained by Eq. (7).

WO algorithm

WO algorithm was selected across other meta-heuristic mechanisms due to that could balance exploitation (local search), exploration (global search) that is important to solve complicated issues of optimization such as WSNs node coverage. In spite of the popularity, ACO, GA and PSO normally not enough solution space exploration, experience premature convergence. WO, inspired by evading predators, eating, walrus motion, takes a more holistic strategy to such restrictions. Through mimicking walrus migration for better adjustments, WO develops abilities of global search via complete search space exploration. Step of exploitation locally modifies responses, replicating the way walruses transfer for escaping/ eating predators, assuring convergence to optimum response. Walrus, the broad aquatic animal with tails, would live with seawater in cold water in Northern Hemisphere. Big adults' whiskers and tusks causes them to be simple for identification. In general, walruses are great animals who look for benthic bivalve mollusks for nourishment on ocean ice. In general, tusks are the most considerable animal attribute that is greatly long. They are broad canines who are in the two female and male animals also could raise to 1 m and weigh 5.4 kg. In nighttime season, walruses' intention for travelling approximately to outliers/stony shores due to climate warms, ice become dissolved. Such motions are greatly intense and include big get-togethers. Polar bear as well as Killer whale refer to dual natural predators for walruses owing to tusks and dimensions. Walruses illustrate smart manner in daily tasks and social dealings and. 3 smart tasks are prominent as being the most-clearest:

a. Helping persons to use below technique of family member by developed tusks: Via looking for the way, the algorithm was directed close to the highest feasible areas by retaining the greatest population member way. Basic walrus is considerable to use the developed tusk and causing other walruses. Such methods contain traveling walruses which notably edit the condition. Ability of mechanism for global search was increased through pretending such big motions.
b. Migration near rocky beaches. Walrus's migration is basically because of warming a common manner called temperatures. They dynamically transfer in present way and go approximate to rocky peaks/seashores. Other conditions of walruses are taken migration targets in WO. Each of such conditions is directed out randomly, walrus moves here. WO framework controls the strategy for increasing global searching and diagnosis ability. Technique of foraging is used by the sturdiest walrus that differs from migrant program that upgrade way of population is not allowed to trust the unique discrete, like greatest member of population. The upgrade process avoids mechanism from delaying local aims, soon convergence.
c. Battle/escape from predators: When fighting the predators such as polar bears and killer whales, walruses apply strategy of chasing. Function of chasing that occurs in a small region, slowly shifts condition of walrus. WO is the amount for looking for near, superior solutions congregation feat was developed through recreating slight walrus functions through viewing for good conditions in fight.

3. Results and Discussion

Simulation environment

Adjustments of simulation are decided in an area where the presented mechanism is assumed to be operational. 2020 version of MATLAB software is installed on system with of 2 gigabytes of RAM, a 1TB hard disk, an Intel i3 with a CPU running at 3.07 GHz, and Windows 10 configuration.

A. Parameters and scenarios of simulation

The area of working with dimensions of 100 x 100 square meters is taken in scenarios. Number of 100 and 300 nodes with basic energy of 0.5 joules are shared randomly in an area and the BS is placed out of area of working with cooperations (50,50) on Fig.2, also it is marked as the red circle. These scenario simulation parameters could be observed in Table 1. These examination outcomes are provided in Fig. 3(a). In presented algorithm, clustering usage given the best WO has developed use of energy in network of sensor. Fig. 3(a) illustrates outcomes achieved algorithms comparison in case of parameters of network life. Based on outcomes, presented algorithm has developed FND, HND and LND amounts. Dead nodes' number in the first scenario, energy used in the first scenario and medium left energy in Figs. 3(b) to 3(c) illustrate presented technique effectiveness comparison with base techniques.

The network, parameters of simulation as well as energy of radio are illustrated in Table 1. Network is developed with 100 nodes with 3 energy heterogeneity classes like, superior, developed, usual nodes. Nodes' fraction energy and value are shown in Table 1. Parameters of WO that particularly illustrate amounts of particle size, starting simulations and other parameters number for WO tasks' run for selecting CH, are shown in Table 2. Parameters' adjustments' reason with amounts considered in Table 1 is using similar platform for assessing presented algorithm performance in contrary to other algorithms.

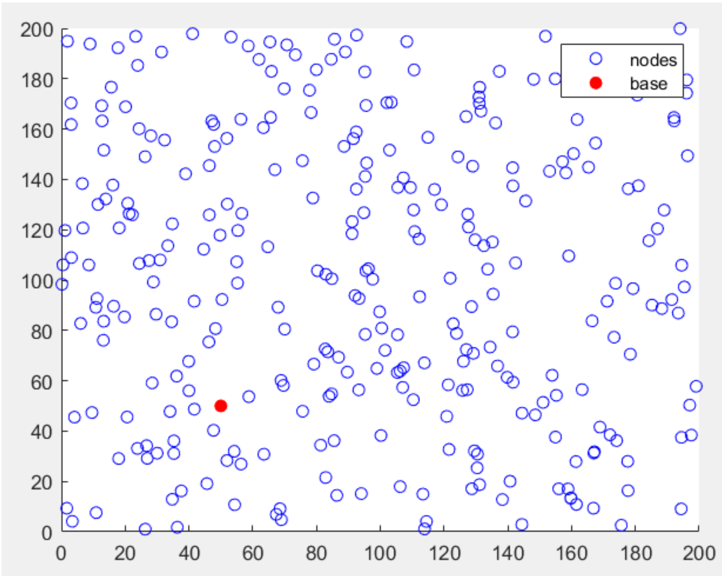


Figure 2. Simulation environment of the first scenario.

Table 2. Simulation parameters.

Network model and WO parameters	Values
The size of the network area	100 x 100 square meters
Number of nodes (N)	100, 300
Number of data sinks	1
Initial energy of nodes (in Joules) (E_0)	0.5

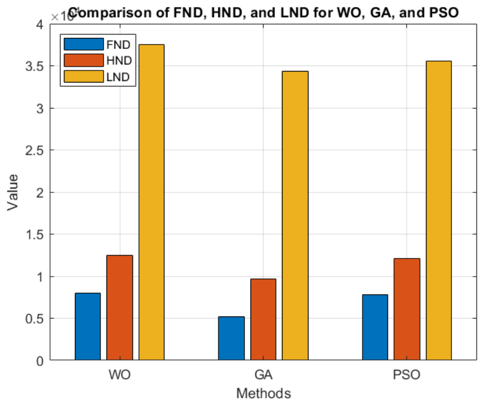
Node type	Normal nodes
Energy required to operate the transmitter and receiver E_{elc}	50nJ/bit
Threshold distance (d_0)	87 meters
Reinforcement energy required for longer distance $d \le d_0$	$10\, pJ / bit / m^2$
Reinforcement energy required for less distance $d \succ d_0$	$0.0013\, pJ / bit / m^4$
Energy consumption occurs while data aggregation occurs (E_{da})	$5nJ / bit / signal$
Data packet size	2000 bits
Population	30
Initial speed	0
Alpha	0.9
Beta	0.4
gamma	0.7
Maximum iteration	100

B. Developed technology comparison algorithms

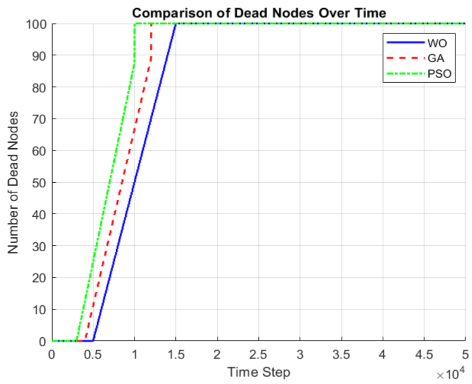
The reasonable performance of presented technique in contrary with meta-heuristic methods for validating usage of WO algorithm and acting in various functions of fitness as well as various approaches of routing. Three scenarios are taken in present assessment. The main GA and PSO mechanisms are taken for assessing presented technique performance.

C. The first scenario

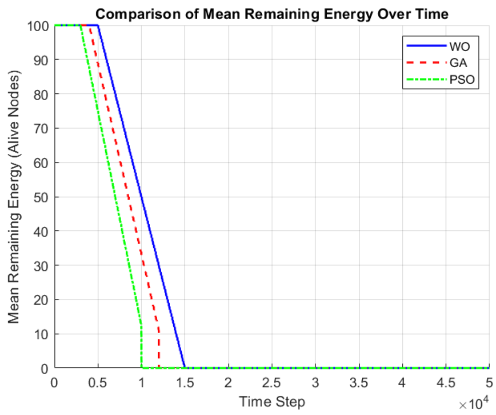
The first scenario we take where BS is maintained out of domain. Sensor nodes number is 100 and with basic energy of 0.5 joules, randomly they are shared in region and network environment is 100*100. Hybrid simulations are carried out and medium outcomes are reported. Outcomes are analyzed given the metrics of performance. Four various metrics of performance (such as (a) network life; (b) dead nodes number vs. cycles; (c) residual energy of network; (d) energy use of network is applied for outcomes' report.



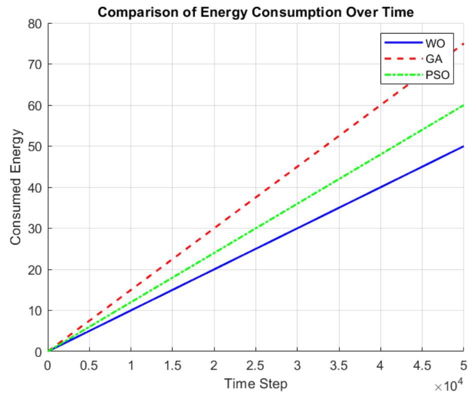
(a)



(b)



(c)



(d)

Figure 3. Comparison of the efficiency of the proposed method with the basic methods in the first scenario a) comparison of the network lifetime b) comparison of dead nodes versus nodes c) comparison of the remaining energy of the network d) comparison of the consumed energy of the network.

Figure 3 includes four comparison charts demonstrating the performance of three different algorithms (WO, GA, and PSO) in various settings. A thorough examination of each sub-diagram is provided below: In Figure 3(a), the value of FND represents the time when the first network node loses energy. WO outperforms GA and PSO due to its greater FND value. The HND value indicates the time when half of the network nodes lose energy. The value of HND for WO remains greater than GA and PSO, indicating that the network is more stable with this strategy. The LND number represents the time when the network's last node goes offline.

In this scenario, WO performs better and demonstrates that network energy is used more efficiently. Figure 3(b) displays the number of dead nodes over time. The associated curve (WO) demonstrates that this approach was able to maintain the nodes alive for an extended period of time. PSO performs the poorest because nodes break more quickly. GA serves a purpose in between the two. Figure 3(c) looks at the average residual energy of nodes over time. The WO curve shows that the nodes consume energy more efficiently since they conserve more energy over time than other methods. PSO has the lowest residual energy, indicating inefficient energy consumption in this method. GA outperforms PSO but is still weaker than WO. Figure 3(d) shows the quantity of energy consumed over time. WO has a smaller slope, indicating more efficient energy utilization. GA uses more energy, followed by PSO. A steeper slope in GA and PSO suggests higher energy usage in these algorithms. The WO algorithm outperforms GA and PSO in terms of energy management and network stability. The GA algorithm performs the worst in most criteria, indicating that its optimization is less efficient than the other two approaches. PSO has a medium performance, which is better than GA but not as good as WO.

D. The second scenario

The second scenario we take where BS is maintained is out of domain and sensor nodes number 300 with basic energy of 1J are shared randomly in area and network domain is 100*100.

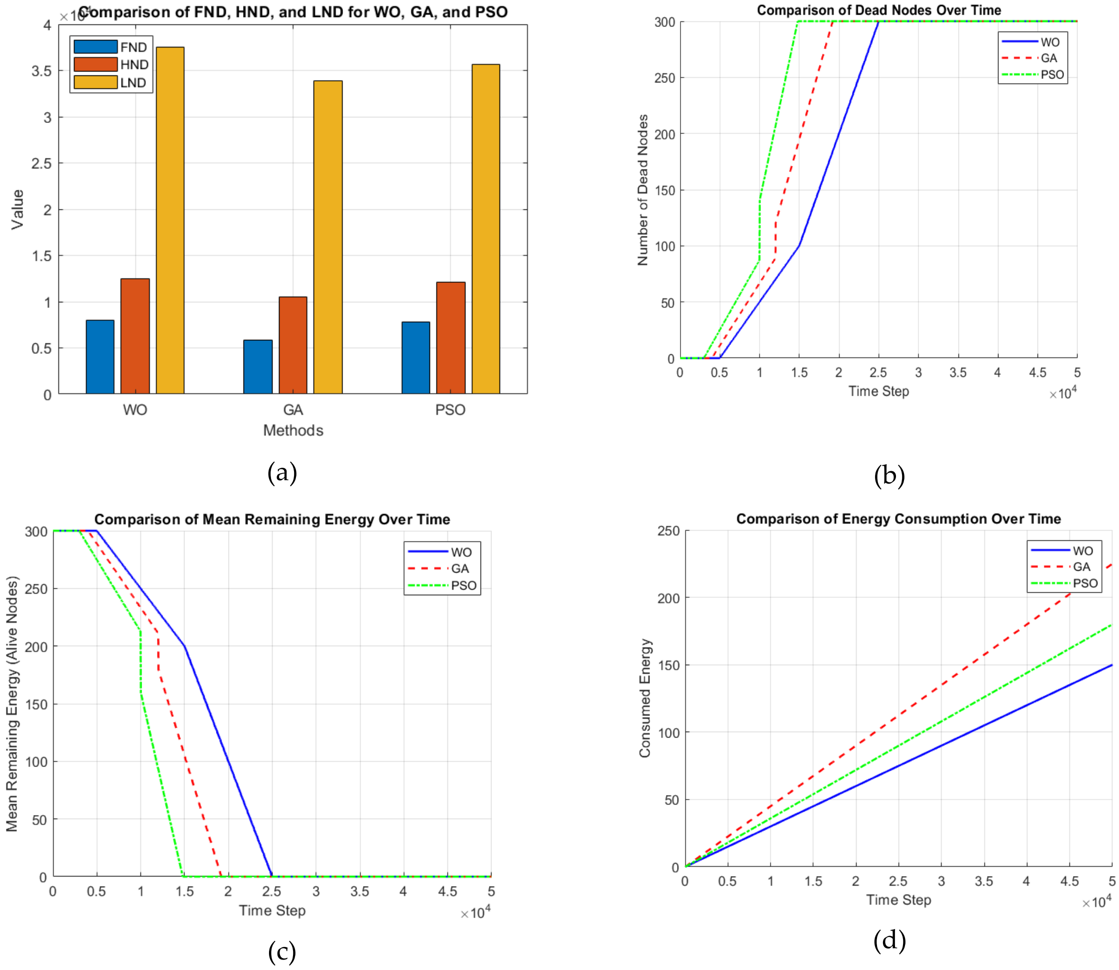
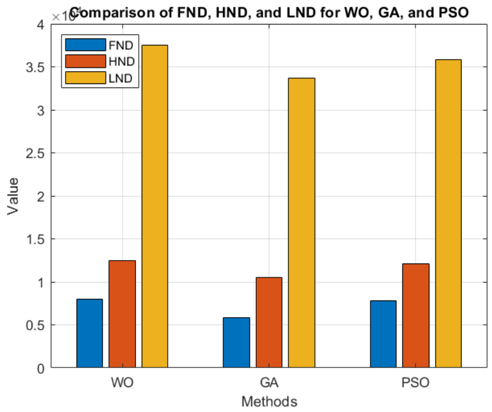


Figure 4. Comparison of the efficiency of the proposed method with the basic methods in the second scenario a) comparison of the network lifetime b) comparison of dead nodes versus nodes c) comparison of the remaining energy of the network d) comparison of the consumed energy of the network.

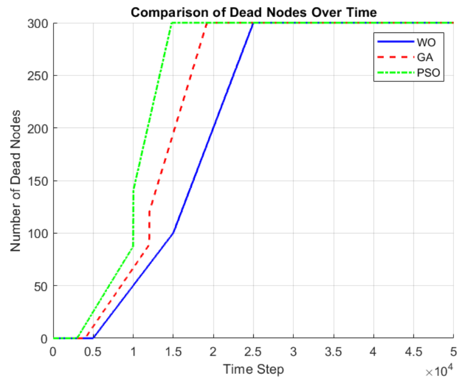
If we increase the number of nodes from 100 to 300, the algorithms' behavior may effect network stability, energy management, and node dead time. The time it takes for the first node to die may grow as the number of nodes increases, because energy consumption is often better dispersed in networks with more nodes. The WO algorithm still outperforms PSO and GA in terms of delaying the death of the first node since they typically have policies in place to distribute the load evenly among the nodes (fig. 4(a)). GA may still have a shorter time for FND in this case, as evolutionary optimization is typically less stable at higher scales. The HND grows with the number of nodes and is determined by a variety of parameters, including energy management and the algorithm's work distribution efficiency. The WO algorithm remains superior, and half of the nodes fail at a slower rate. GA outperforms WO in terms of node count because GA typically performs better in larger, more dynamic networks. PSO will continue to perform less well than the other two algorithms (fig. 4(b)). As the number of nodes grows, the dead time of the final node decreases because energy resources are dispersed more evenly throughout the network. WO still has the longest LND time because this algorithm often provides more efficient energy use. GA still ranks second and is close to WO, but it cannot match the LND time of the WO algorithm (fig. 4(c)). This PSO algorithm's LND time is anticipated to be much shorter because PSO optimization is less successful for larger networks. WO will also have superior energy management, as its primary purpose is to spread the load evenly among the nodes. PSO outperforms WO on a wider grid scale, although it uses energy faster. Typically, the energy usage in this GA algorithm is less ideal (fig. 4(d)), and this issue worsens as the network scale increases.

E. The third scenario

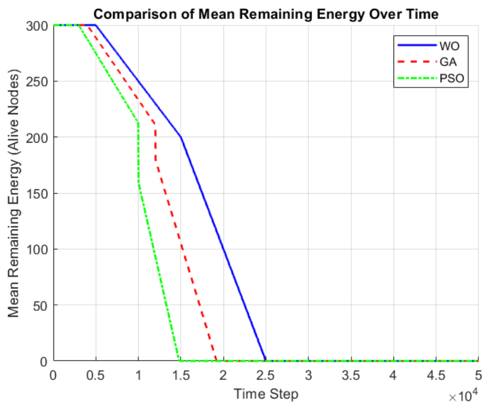
The third scenario which we take where BS is maintained out of domain and sensor nodes number of 300 with basic energy of 1J are shared randomly in region and network domain is 100*100.



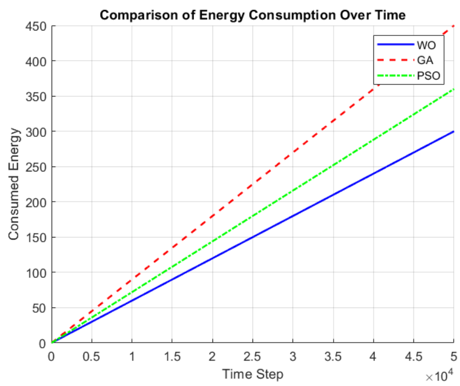
(a)



(b)



(c)



(d)

Figure 5. Comparison of the efficiency of the proposed method with the basic methods in the third scenario a) comparison of the network lifetime b) comparison of dead nodes versus nodes c) comparison of the remaining energy of the network d) comparison of the consumed energy of the network.

Increasing each node's initial energy from 0.5J to 1J can significantly impact network performance and FND, HND, and LND values. In this situation, as the beginning energy increases, so does the first node's dead time, as the nodes have more energy to accomplish jobs. Because of the uniform load distribution of WO, the nodes' energy is utilized uniformly, resulting in an increase in time. FND was compared to other methods. PSO outperforms GA, but falls short of WO in terms of optimal energy allocation (fig. 5(a)). Because of the GA algorithm's shortcoming in energy management, the first node is destroyed before the other two techniques.

Increasing the initial energy strengthens the network's resistance to node mortality and extends the HND period. WO Because of its efficient energy utilization, this algorithm can maintain half of the nodes alive for an extended period of time. Although GA improves performance, half of the nodes still die earlier than WO. PSO remains inferior to GA and WO owing to imbalanced task distribution and higher energy usage. Increasing the starting energy will postpone the death of the last node. The improved performance of this WO algorithm in uniform energy distribution allows the last node to survive for a longer period of time. The death of the last node in this PSO algorithm happens later than in GA, yet it still falls short of WO's performance (fig. 5(b)). Because of GA's limitation in optimal energy use, the LND time in this algorithm will be shorter than the other two techniques.

The WO method is based on a uniform distribution of load and work across nodes. This feature balances energy usage across nodes, whereas PSO and GA focus less on load balancing. WO employs strategies to prevent undue strain on specific nodes, hence extending network lifetime. With 300 nodes, WO is more efficient in managing network resources than other methods. PSO may function similarly to WO on large scales, but it cannot achieve the energy balance of WO (fig. 5(c)). Because of its simple and low energy consumption design, the WO algorithm is more compatible with wireless networks than PSO and GA, which are more sophisticated. Increasing the initial energy from 0.5J to 1J improves network performance across all algorithms (fig. 5(d)). Because of improved load distribution and balanced energy usage, the WO algorithm continues to outperform in terms of network stability and FND, HND, and LND time.

F. Data analysis

From outcomes of simulation in whole 3 scenarios, this could be observed that presented technique illustrates important development in various metrics of performance, known as number used and medium left energy, dead nodes, life of network. Particular reasons for such development after comprehensive simulation analysis inspection are featured to: medium residual energy as well as dead nodes number are developed because of optimum CH selection that is performed via 5 selection elements, for protecting energy of node with sensors aid. Life of network is developed because of optimum CH selection and routing performed by WO.

4. Conclusion

Here, we provided the presented technique to choose CH in WSNs domain that could solve stability issues in case of efficiency, immediate concerns, life and stability of network. WO was applied in fitness function combination in case of 5 various parameters that briefly include nodes' number, distance, left energy, ECR, medium energy. At last, such examined parameters were fed by presented technique and their performance in various present algorithms was assessed with various metrics of performance. From test outcome, this was seen that presented technique is achieved compared to their opposite terms. Also, comparing performance with present element models proves presented technique efficiency. The assessment could be applied as algorithm of support for system of network for their algorithm validation.

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